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Blind and semi-blind ML detection for space-time block coded OFDM wireless systems

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Abstract

This paper investigates the joint maximum-likelihood (ML) data detection and channel estimation problem for space-time-block-coded (STBC) OFDM wireless systems with general constellation modulations. An efficient low-complexity algorithm is proposed based on recursive least squares (RLS) that renders exact ML estimates of both channel and the data. The wireless channel is assumed to be stationary within two OFDM symbols but is allowed to vary after every two OFDM symbols; thus making it suitable for fast fading scenarios. The proposed methodology combines the advantages of both STBC, which gives full diversity gain and OFDM which circumvents the inter-symbol-interference (ISI) problem. The computational complexity of algorithm becomes critical at low signal-to-noise-ratio (SNR) as the number of OFDM carriers and constellation size are increased especially in multiple antenna systems. A new framework for reducing the complexity is proposed based on subcarrier reordering and decoding the carriers with different levels of confidence using a suitable reliability criterion. This newly devised approach enables the algorithm to reliably track the wireless Rayleigh fading channel in semi-blind fashion without requiring any channel statistics to be known. Simulation results demonstrate the effectiveness of blind and semi-blind algorithms over frequency selective channels with different fading characteristics.

Keywords: Blind ML detection; OFDM; Alamouti coding; Recursive Least Squares

1 Introduction

The increasing demand for higher data rates in recent years has called for transmissions over a broadband wireless channel which is frequency selective. The wireless channel is thus prone to inter-symbol-interference (ISI) which severely degrades the system performance and requires complex equalization techniques at the receiver side. The orthogonal-frequency-division multiplexing (OFDM) has emerged as the most promising scheme to combat ISI and improve system performance. OFDM essentially transforms a broadband channel into a number of parallel narrowband channels using a cyclic prefix (CP) of appropriate length and renders simple one tap channel equalizer for each OFDM subcarrier [1]. Therefore, it has been adopted in many existing wireless standards, such as IEEE 802.11, IEEE 802.16, DAB, DVB, ADSL etc., and is also a potential candidate for many future wireless standards. Besides OFDM, the spatial dimensions in wireless communications are often exploited to further enhance the system capacity and /or improve the transmission reliability by employing multiple antennas at the transmitter and/or receiver. This offers many advantages over single antenna systems including multiplexing gain and diversity gain [2]. Of several diversity schemes available in the literature, the Alamouti scheme [3] with two transmit and one receive antenna is optimum in both capacity and the diversity. Alamouti coding achieves full spatial diversity at full transmission rate for any signal (real or complex) constellation and offers very simple receiver structures. However, to decouple the signals at receiver side via simple decoding, the Alamouti scheme requires the channel between each transmit-receive antenna to be constant over two consecutive OFDM symbols. When dealing with frequency selective channel, Alamouti scheme has to be implemented over the block level. Among various block coding structures, single-carrier frequency-domain-equalized (SC-FDE) [4] is the most promising one due to its superior performance.

In many wireless communications studies, it is often assumed that channel state information (CSI) is available at the receiver side for coherent data detection. This assumption is certainly not realistic. The current standards use pilot symbols to estimate the channel thus sacrificing bandwidth which otherwise would have been available for data transmission. In high mobility wireless systems, the channels may even change so rapidly that this approach will become infeasible. Blind or semi-blind detection over the time-varying wireless channels has shown to enhance the system performance considerably [5], [6].

There are numerous blind estimation and equalization techniques available in the literature, namely; subspace-based methods [7], [8], second-order-statistics [9], cholesky factorization [10] or iterative methods [11]. These methods either suffer from slow convergence, higher computational costs or assume channel to be stationary over several OFDM blocks. These drawbacks make ML based approaches e.g. [12],[13] more attractive due to their fast convergence despite having the higher computational cost. Usually suboptimal techniques are employed to reduce computational cost by restricting the search space of exhaustive ML search. These suboptimal techniques, however, are applicable to specific constant modulus constellations [14], [15]. Recently in [16] and [17], the authors have proposed a low-complexity blind ML method for general constellations for single-input-multiple-output (SIMO) and single-input-single-output (SISO) systems, which form the basis of current paper.

Contributions: In this paper we extend the previous algorithm for SISO OFDM systems [17] to transmit diversity scheme of Alamouti in order to gain full advantage of both OFDM and Alamouti or spatial diversity scheme. Parallelizing the results and discussions therein, we derive blind ML algorithm for blind channel estimation and data detection. The proposed algorithm offers low complexity, fast convergence, works for signals drawn from general modulation constellations and doesn't require any channel statistics to be known. The complexity of proposed blind algorithm becomes critical in multi-antenna systems as the number of OFDM carriers and constellation size are increased especially in the low SNR regime. However, when employed in semi-blind mode for channel estimation where initial training or pilot symbols are used at the start of transmission, a complete new framework for complexity reduction is adopted. This framework is based on reliably decoding the carriers by computing the vector-wise likelihood ratio first suggested in [18]. By supplying the algorithm with reordered carriers according to their reliability index, the backtracking is minimized which is the major source of complexity. In higher SNR regimes the probability of backtracking is almost zero [17] and thus the complexity of algorithm becomes very low.

Organization of paper: Section 2 describes the Alamouti coded OFDM system model with frequency selective time-variant channels and Section 3 describes proposed blind ML algorithm. In Section 4, a low complexity variant of blind ML algorithm is derived by exploiting the structure of DFT matrix. To further reduce the complexity of the algorithm, we propose in Section 5, a semi-blind variant of our algorithm. Simulation results are detailed in Section 6. We conclude the paper in Section 7.

Notation: We use lower case letters x, to denote scalars, lower case boldface $\mathbf{x}$ to denote (column) vectors and $\mathbf{x}(i)$ to denote individual entries of a vector. Matrices are denoted by upper boldface letters $\mathbf{X}$ whereas the calligraphic notations $\boldsymbol{\mathcal{X}}$ is reserved for vectors in frequency domain. We also use $\mathbf{x}_{(i)}$ to represent a partial vector consisting of first i elements of $\mathbf{x}$. $(.)^T$, $(.)^*$ and $(.)^H$ represent transpose, conjugate and conjugate transpose (hermitian) operations respectively. $\langle\hat{\boldsymbol{\mathcal{X}}}(k)\rangle$ will denote the hard decoding decision that maps $\hat{\boldsymbol{\mathcal{X}}}(k)$ to $\boldsymbol{\mathcal{X}}(k)$. The discrete Fourier Transform (DFT) and inverse DFT (IDFT) matrices are denoted by $\mathbf{Q}$ and $\mathbf{Q}^H$ respectively, where we define $\mathbf{Q}$ as $q_{l,k} = e^{-j2\pi lk/N}$ with $l,k = 0,1,2,\cdots,N-1$. The notation $\|\mathbf{a}\|^2_{\mathbf{B}}$ represents weighted norm defined as $\|\mathbf{a}\|^2_{\mathbf{B}} = \mathbf{a}^H\mathbf{B}\mathbf{a}$.

2 System model

Consider a single user OFDM system with two-transmit and one-receive antenna as shown in Fig. 1. The two channels from two transmit antennas to the receive antenna are both frequency selective and are modelled as finite impulse response (FIR) filters. We assume that both channels are independent Rayleigh-fading channels of maximum length L and that OFDM cyclic prefix (CP) length is at least L-1 to avoid ISI.

Let $\boldsymbol{\mathcal{X}}$ represent information symbols and that OFDM system has N-sub carriers so that after IFFT operation the OFDM symbol can be written as:

$$\mathbf{x} = \sqrt{N}\mathbf{Q}^H\boldsymbol{\mathcal{X}} \tag{1}$$

where $\mathbf{Q}$ is DFT matrix with $[\mathbf{Q}]_{l,k} = e^{-j2\pi lk/N}$. Let the n^{th} symbol of k^{th} transmitted block from antenna i ($= 1$ or 2) be denoted by $x_i^{(k)}(n)$, with $n = 0,1,\cdots,N-1$. At times $k = 0,2,4,\cdots$ pair of blocks $x_1^{(k)}(n)$ and $x_2^{(k)}(n)$ are generated according to following rule [4]:

$$\begin{aligned} x_1^{(k+1)}(n) &= -x_2^{*(k)}((n))_N \\ x_2^{(k+1)}(n) &= x_1^{*(k)}((n))_N \end{aligned} \tag{2}$$

where, $(.)_N$ is modulo N operation. Each antenna transmits a data block of length N according to STBC scheme after appending the CP. Adding CP eliminates interblock interference and converts linear convolution into circular convolution. In the presence of AWGN, the received data blocks over two consecutive time instants after discarding the CPs can be written as:

$$\mathbf{y}^{(j)} = \sqrt{\rho}\mathbf{H}_1\mathbf{x}_1^{(j)} + \sqrt{\rho}\mathbf{H}_2\mathbf{x}_2^{(j)} + \mathbf{n}^{(j)}, j = k, k+1 \tag{3}$$

where ρ is the SNR, $\mathbf{H}_1$ and $\mathbf{H}_2$ are circulant channel matrices from transmit antenna-1 and transmit antenna-2 to receive antenna respectively and $\mathbf{n}$ is additive white circular symmetric Gaussian noise with $\mathbf{n} \sim N(\mathbf{0}, \mathbf{I})$. In equation 3, we also assumed that channel is constant over two consecutive OFDM blocks at time instants k and $k+1$. Specifically, the structure of two circular channel matrices is:

$$\mathbf{H}_i = \begin{pmatrix} h_i(0) & 0 & \cdots & h_i(L-1) & \cdots & h_i(1) \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ h_i(L-2) & \cdots & h_i(0) & 0 & \cdots & h_i(L-1) \\ h_i(L-1) & h_i(L-2) & \cdots & h_i(0) & 0 & \vdots \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & h_i(L-1) & h_i(L-2) & \cdots & h_i(0) \end{pmatrix}$$

and where,

$$\mathbf{h}_i = \begin{bmatrix} h_i(0) & h_i(1) & \cdots & h_i(L-1) \end{bmatrix}^T \tag{4}$$

represents the impulse response sequence of i^{th} channel matrix. At the receiver side, the frequency domain received symbols after FFT operations are obtained as:

$$\boldsymbol{\mathcal{Y}}^{(j)} = \sqrt{\rho}\mathbf{\Lambda}_1\boldsymbol{\mathcal{X}}_1^{(j)} + \sqrt{\rho}\mathbf{\Lambda}_2\boldsymbol{\mathcal{X}}_2^{(j)} + \boldsymbol{\mathcal{N}}^{(j)}, j = k, k+1 \tag{5}$$

where $\boldsymbol{\mathcal{X}}_i^{(j)} = \frac{1}{\sqrt{N}}\mathbf{Q}\mathbf{x}_i$, $\mathbf{\Lambda}_i = \mathbf{Q}\mathbf{H}_i\mathbf{Q}^H$, are diagonal matrices whose entries are N-point DFT of $\mathbf{h}_i$ after zero-padding and $\boldsymbol{\mathcal{N}}^{(j)} = \frac{1}{\sqrt{N}}\mathbf{Q}\mathbf{n}_j$. Expanding 5) and using DFT properties we get:

$$\begin{aligned} \boldsymbol{\mathcal{Y}}^{(k)} &= \sqrt{\rho}\mathbf{\Lambda}_1\boldsymbol{\mathcal{X}}_1^{(k)} + \sqrt{\rho}\mathbf{\Lambda}_2\boldsymbol{\mathcal{X}}_2^{(k)} + \boldsymbol{\mathcal{N}}^{(k)}, \\ \boldsymbol{\mathcal{Y}}^{(k+1)} &= \sqrt{\rho}\mathbf{\Lambda}_1\boldsymbol{\mathcal{X}}_1^{(k+1)} + \sqrt{\rho}\mathbf{\Lambda}_2\boldsymbol{\mathcal{X}}_2^{(k+1)} + \boldsymbol{\mathcal{N}}^{(k+1)} \end{aligned} \tag{6}$$

By stacking the received data symbols over consecutive intervals in one column and DFT channel coefficients, (6) can be written in matrix-vector notation as:

$$\begin{bmatrix} \boldsymbol{\mathcal{Y}}^{(k)} \\ \boldsymbol{\mathcal{Y}}^{(k+1)} \end{bmatrix} = \sqrt{\rho} \begin{bmatrix} \operatorname{diag}\left(\boldsymbol{\mathcal{X}}_1^{(\mathrm{k})}\right) & \operatorname{diag}\left(\boldsymbol{\mathcal{X}}_2^{(\mathrm{k})}\right) \\ -\operatorname{diag}\left(\boldsymbol{\mathcal{X}}_2^{*(\mathrm{k})}\right) & \operatorname{diag}\left(\boldsymbol{\mathcal{X}}_1^{*(\mathrm{k})}\right) \end{bmatrix} \begin{bmatrix} \boldsymbol{\mathcal{H}}_1 \\ \boldsymbol{\mathcal{H}}_2 \end{bmatrix} + \begin{bmatrix} \boldsymbol{\mathcal{N}}^{(k)} \\ \boldsymbol{\mathcal{N}}^{(k+1)} \end{bmatrix} \tag{7}$$

where, $\boldsymbol{\mathcal{H}}_i = diag(\boldsymbol{\Lambda}_i) = \mathbf{Q} \begin{bmatrix} \mathbf{h}_i \\ \mathbf{0} \end{bmatrix}$. Let $\mathbf{A}^H$ consists of first L columns of $\mathbf{Q}$, then

$$\boldsymbol{\mathcal{H}}_i = \mathbf{A}^H \mathbf{h}_i \text{ and } \mathbf{h}_i = \mathbf{A}\boldsymbol{\mathcal{H}}_i \tag{8}$$

This allows us to rewrite (7) as:

$$\begin{aligned} \underbrace{\begin{bmatrix} \boldsymbol{\mathcal{Y}}^{(k)} \\ \boldsymbol{\mathcal{Y}}^{(k+1)} \end{bmatrix}}_{\boldsymbol{\mathcal{Y}}} = \sqrt{\rho} & \underbrace{\begin{bmatrix} \operatorname{diag}\left(\boldsymbol{\mathcal{X}}_1^{(\mathrm{k})}\right)\mathbf{A}^{\mathrm{H}} & \operatorname{diag}\left(\boldsymbol{\mathcal{X}}_2^{(\mathrm{k})}\right)\mathbf{A}^{\mathrm{H}} \\ -\operatorname{diag}\left(\boldsymbol{\mathcal{X}}_2^{*(\mathrm{k})}\right)\mathbf{A}^{\mathrm{H}} & \operatorname{diag}\left(\boldsymbol{\mathcal{X}}_1^{*(\mathrm{k})}\right)\mathbf{A}^{\mathrm{H}} \end{bmatrix}}_{\mathbf{X}_a} \underbrace{\begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \end{bmatrix}}_{\mathbf{h}} \\ & + \underbrace{\begin{bmatrix} \boldsymbol{\mathcal{N}}^{(k)} \\ \boldsymbol{\mathcal{N}}^{(k+1)} \end{bmatrix}}_{\boldsymbol{\mathcal{N}}} \end{aligned} \tag{9}$$

or even more compactly as:

$$\boldsymbol{\mathcal{Y}} = \sqrt{\rho}\mathbf{X}_a\mathbf{h} + \boldsymbol{\mathcal{N}} \tag{10}$$

where $\boldsymbol{\mathcal{Y}}$ and $\boldsymbol{\mathcal{N}}$ are $2N$ x 1 observed data and noise vectors respectively, $\mathbf{X}_a$ is a $2N$ x $2L$ data matrix, which we will refer to as *Alamouti matrix*, and $\mathbf{h}$ is a $2L$ x 1 composite channel vector. This model can be easily transformed to the case of SISO OFDM system model of [17] by replacing $\mathbf{X}_a$ with N x N square matrix diag($\boldsymbol{\mathcal{X}}$) containing N data symbols on its diagonal. Specifically the SISO model corresponding to (10) is given by:

$$\boldsymbol{\mathcal{Y}} = \sqrt{\rho}\operatorname{diag}(\boldsymbol{\mathcal{X}})\mathbf{h} + \boldsymbol{\mathcal{N}} \tag{11}$$

where $\boldsymbol{\mathcal{Y}}$ and $\boldsymbol{\mathcal{N}}$ are N-dimensional received OFDM symbol and noise vector respectively while $\mathbf{h}$ is the length-L SISO channel vector. Based on the model given in (10), the task of receiver is to jointly estimate the channel vector $\mathbf{h}$ and the data vector $\boldsymbol{\mathcal{X}} = \begin{bmatrix} \boldsymbol{\mathcal{X}}_1^T & \boldsymbol{\mathcal{X}}_2^T \end{bmatrix}^T$ given the received symbol vector $\boldsymbol{\mathcal{Y}}$.

3 Joint ML solution

Considering the data model in (10), the joint ML solution of channel estimation and data detection problem can be seen as minimization of following objective function (omitting the subscript a):

$$\begin{aligned} J_{ML} &= \min_{\mathbf{h}, \boldsymbol{\mathcal{X}} \in \Omega^{2N}} \left\{ \|\boldsymbol{\mathcal{Y}} - \sqrt{\rho}\mathbf{X}\mathbf{h}\|^2 \right\} \\ &= \min_{\mathbf{h}, \boldsymbol{\mathcal{X}} \in \Omega^{2N}} \left\{ \underbrace{\|\boldsymbol{\mathcal{Y}}_{(i)} - \sqrt{\rho}\mathbf{X}_{(i)}\mathbf{h}\|^2}_{M_{\mathcal{X}_{(i)}}} + \sum_{j=i+1}^{N} \|\boldsymbol{\mathcal{Y}}(j) - \sqrt{\rho}\mathbf{X}_{(j)}\mathbf{h}\|^2 \right\} \end{aligned} \quad (12)$$

where Ω^{2N} denotes all possible $2N$-dimensional signal vectors and the rest are defined as follows:

$\mathbf{X}_{(i)} = \begin{bmatrix} \text{diag}\left(\boldsymbol{\mathcal{X}}_{1(\text{i})}^{(\text{k})}\right)\mathbf{A}_{(\text{i})}^{\text{H}} & \text{diag}\left(\boldsymbol{\mathcal{X}}_{2(\text{i})}^{(\text{k})}\right)\mathbf{A}_{(\text{i})}^{\text{H}} \\ -\text{diag}\left(\boldsymbol{\mathcal{X}}_{2(\text{i})}^{*(\text{k})}\right)\mathbf{A}_{(\text{i})}^{\text{H}} & \text{diag}\left(\boldsymbol{\mathcal{X}}_{1(\text{i})}^{*(\text{k})}\right)\mathbf{A}_{(\text{i})}^{\text{H}} \end{bmatrix}$ is a partial Alamouti-matrix of dimension $2i$ x $2L$.

$\boldsymbol{\mathcal{Y}}_{(i)} = \begin{bmatrix} \boldsymbol{\mathcal{Y}}_{(i)}^{(k)} \\ \boldsymbol{\mathcal{Y}}_{(i)}^{(k+1)} \end{bmatrix}$ is a partial data vector of dimension $2i$ x 1.

In above definitions the partial matrix $\mathbf{A}_{(i)}^H$ consists of first i rows of $\mathbf{A}^H$. Also in (12) we have defined the cost associated with the partial data sequences as $M_{\mathcal{X}_{(i)}}$. Moreover, it should be noted that partial Alamouti-matrix will be a function of first i data points only.

We proceed to find the Joint ML solution to (12) using the following lemma. *Lemma*: Let R represent the optimal value of the objective function in (12). If $M_{\mathcal{X}_{(i)}} > R$, then $\boldsymbol{\mathcal{X}}_{(i)}$ doesn't correspond to the ML solution $\hat{\boldsymbol{\mathcal{X}}}_{(i)}^{ML}$ of (12). In other words, for any estimate $\hat{\boldsymbol{\mathcal{X}}}_{(i)}$ to correspond to the ML solution, we should have $M_{\mathcal{X}_{(i)}} < R$. This lemma was proved in [17] for SISO case. We extend it here to the multi antenna case. This lemma suggests that at each subcarrier frequency i, we can make a guess of new value of $\boldsymbol{\mathcal{X}}(i) = \begin{bmatrix} \mathcal{X}_1(i) & \mathcal{X}_2(i) \end{bmatrix}^T$ and use that along with previous estimates to construct $\hat{\boldsymbol{\mathcal{X}}}_{(i)}$ and $\hat{\mathbf{X}}_{(i)}$. Then estimate $\mathbf{h}$ to minimize the following cost function:

$$M_{\hat{\mathcal{X}}_{(i)}} = \min_{\mathbf{h}} \left\{ \|\boldsymbol{\mathcal{Y}}_{(i)} - \sqrt{\rho}\hat{\mathbf{X}}_{(i)}\mathbf{h}\|^2 \right\} \tag{13}$$

and calculate the resulting $M_{\hat{\mathcal{X}}_{(i)}}$. If $M_{\hat{\mathcal{X}}_{(i)}} < R$, then proceed to the next subcarrier $i+1$, otherwise backtrack and change the guess of $\boldsymbol{\mathcal{X}}(j)$ for some $j \leq i$. This approach however is not valid for $i \leq L$ because $\mathbf{X}_{(i)}$ will be full rank for any choice of $\boldsymbol{\mathcal{X}}_{(i)}$ and therefore the LS solution of $\mathbf{h}$ would result in a trivial(zero) minimum mean square estimate (MMSE). To obtain a non-trivial value of $M_{\hat{\mathcal{X}}_{(i)}}$, we have to use L pilots, but it would defeat our original motive of *blind* estimation.

To get around this problem, we adopt an alternative strategy based on weighted regularized least squares which corresponds to minimizing the maximum *a posteriori* (MAP) objective function:

$$J_{MAP} = \min_{\mathbf{h},\boldsymbol{\mathcal{X}} \in \Omega^{2N}} \left\{ \|\mathbf{h}\|^2_{\mathbf{R}_h^{-1}} + \|\boldsymbol{\mathcal{Y}} - \sqrt{\rho}\mathbf{X}_a\mathbf{h}\|^2 \right\} \tag{14}$$

where $\mathbf{R}_h$ is the block diagonal autocorrelation matrix of the composite channel vector $\mathbf{h}$ i.e. $\mathbf{R}_h = E\left\{\mathbf{h}\mathbf{h}^H\right\}$. The objective function in (14) can be decomposed as follows:

$$\begin{aligned} J_{MAP} = \min_{\mathbf{h}\boldsymbol{\mathcal{X}} \in \Omega^{2N}} \Bigg\{ & \underbrace{\|\mathbf{h}\|^2_{\mathbf{R}_h^{-1}} + \|\boldsymbol{\mathcal{Y}}_{(i)} - \sqrt{\rho}\mathbf{X}_{a(i)}\mathbf{h}\|^2}_{M_{\mathcal{X}_{(i)}}} \\ & + \sum_{j=i+1}^{N} \|\boldsymbol{\mathcal{Y}}(j) - \sqrt{\rho}\mathbf{X}_a(j)\mathbf{h}\|^2 \Bigg\} \end{aligned} \tag{15}$$

So, if we have an estimate $\hat{\boldsymbol{\mathcal{X}}}_{(i-1)}$, the cost function can be written as:

$$M_{\hat{\mathcal{X}}_{(i-1)}} = \min_{\mathbf{h}} \left\{ \|\mathbf{h}\|^2_{\mathbf{R}_h^{-1}} + \|\boldsymbol{\mathcal{Y}}_{(i-1)} - \sqrt{\rho}\hat{\mathbf{X}}_{a(i-1)}\mathbf{h}\|^2 \right\} \tag{16}$$

whose optimum value $\hat{\mathbf{h}}$ and MMSE can be determined [19]. Equations (15) and (16) suggest that if we have a guess of the next data point $\boldsymbol{\mathcal{X}}(i)$, we can express the cost function $M_{\hat{\mathcal{X}}_{(i)}}$ recursively in terms of $M_{\hat{\mathcal{X}}_{(i)}}$ and an additional regressor $\hat{\mathbf{X}}_a(i)$

as follows:

$$\begin{aligned} M_{\hat{\mathcal{X}}_{(i)}} &= \min_{\mathbf{h}} \left\{ \|\mathbf{h}\|^2_{\mathbf{R}_h^{-1}} + \|\boldsymbol{\mathcal{Y}}_{(i)} - \sqrt{\rho}\hat{\mathbf{X}}_{a(i)}\mathbf{h}\|^2 \right\} \\ &= \min_{\mathbf{h}} \left\{ \|\mathbf{h}\|^2_{\mathbf{R}_h^{-1}} + \left\| \begin{bmatrix} \boldsymbol{\mathcal{Y}}_{(i-1)} \\ \boldsymbol{\mathcal{Y}}(i) \end{bmatrix} - \sqrt{\rho} \begin{bmatrix} \hat{\mathbf{X}}_{a(i-1)} \\ \hat{\mathbf{X}}_a(i) \end{bmatrix} \mathbf{h} \right\|^2 \right\} \end{aligned} \tag{17}$$

Equation (17) can be implemented recursively using block version of RLS algorithm [19] with the data vector of dimension 2 x 1 and the regressor matrix of dimension 2 x $2L$ as follows:

$$M_{\hat{\mathcal{X}}_{(i)}} = M_{\hat{\mathcal{X}}_{(i-1)}} + \mathbf{e}_i^H \boldsymbol{\Gamma}_i \mathbf{e}_i \tag{18}$$

$$\hat{\mathbf{h}}_i = \hat{\mathbf{h}}_{i-1} + \mathbf{G}_i \mathbf{e}_i \tag{19}$$

where,

$$\mathbf{e}_i = \boldsymbol{\mathcal{Y}}(i) - \sqrt{\rho}\hat{\mathbf{X}}_a(i)\hat{\mathbf{h}}_{i-1} \tag{20}$$

$$\boldsymbol{\Gamma}_i = \left[\mathbf{I}_2 + \rho \hat{\mathbf{X}}_a(i) \mathbf{P}_{i-1} \hat{\mathbf{X}}_a(i)^H \right]^{-1} \tag{21}$$

$$\mathbf{G}_i = \sqrt{\rho}\mathbf{P}_{i-1}\hat{\mathbf{X}}_a(i)^H \boldsymbol{\Gamma}_i \tag{22}$$

$$\mathbf{P}_i = \mathbf{P}_{i-1} - \mathbf{G}_i \boldsymbol{\Gamma}_i^{-1} \mathbf{G}_i^H \tag{23}$$

The RLS recursions are initialized by

$$M_{\hat{\mathcal{X}}_{(i-1)}} = 0,\ \hat{\mathbf{h}}_{-1} = \mathbf{0} \text{ and } \mathbf{P}_{-1} = \mathbf{R}_h.$$

If R is the optimal value of MAP objective function in (14), then based on above recursive updates we can restrict our search for blind detection of symbols to the partial sequences $\hat{\boldsymbol{\mathcal{X}}}_{(i)}$ such that $M_{\hat{\mathcal{X}}_{(i)}} < R$. *Blind MAP Algorithm* Based on above developments, we can restate the blind algorithm of [17] to find MAP solution of equation (14). It is based on computing the value of cost function from RLS recursions and then comparing it with an optimal value R. The input parameters for the algorithm are: the received channel output over two consecutive intervals

$\boldsymbol{\mathcal{Y}}$, the initial search radius r, the modulation constellation Ω and the 1 x N carrier index vector I.

1 **(Initialize)** Set $i = 1$,$I(i) = 1$, $\hat{\boldsymbol{\mathcal{X}}}(i) = \Omega\big(I(i)\big)$ and construct the *Alamouti matrix* $\hat{\mathbf{X}}_a(i)$.

2 **(Compare with bound)** Compute and store the metric $M_{\hat{\mathcal{X}}_{(i)}}$. If $M_{\hat{\mathcal{X}}_{(i)}} > R$; go to 3; else go to 4.

3 **(Backtrack)** Find the largest $1 \leq j \leq i$ 1such that $I(j) < |\Omega|$. If there exists such j, set $i = j$ and go to 5; else go to 6.

4 **(Increment subcarrier)** If $i < N$, set $i = i + 1, I(i) = 1, \hat{\boldsymbol{\mathcal{X}}}(i) = \Omega\big(I(i)\big)$ and go to 2; else store the current $\hat{\boldsymbol{\mathcal{X}}}_{(N)}$, update $r = M_{\hat{\mathcal{X}}_{(N)}}$ and go to 3.

5 **(Increment constellation)** Set $I(i) = I(i) + 1$ and $\hat{\boldsymbol{\mathcal{X}}}(i) = \Omega\big(I(i)\big)$. Go to 2.

6 **(End/Restart)** If a full-length sequence $\hat{\boldsymbol{\mathcal{X}}}_{(N)}$ has been found in step 4, output it as the MAP solution and terminate; otherwise, double 'r' and go to 1.

The algorithm essentially involves a tree search type mechanism that visits only those branches (i.e. the alphabets here) at each node (i.e. subcarrier here) that satisfy the given constraint $M_{\hat{\mathcal{X}}_{(i)}} < R$. In other words, this constraint serves as a guide which enables algorithm to move back and forth in order to follow the right track and hence produces the true ML solution. The complexity of blind algorithm depends on 1) computing cost function (step 2), which ultimately depends on computation of $2L$ x $2L$ matrix $\mathbf{P}_i$ and 2) Backtracking. In Section 4 we shall see how computation of $\mathbf{P}_i$ can be avoided using the special structure of the DFT matrix. The search space at each node is of dimension $|\Omega|^2$ as compared to $|\Omega|$ for SISO case, where $|\Omega|$ represents the alphabet size. This shows that for a fixed alphabet size, the complexity will increase exponentially with the number of transmit antennas in general. Thus the complexity due to backtracking will ultimately dominate and imperatively needs to be addressed. In Section 5 we shall tackle this issue and see how it can be avoided.

To successfully run the algorithm we require the parameters; SNR ρ, the channel covariance matrix $\mathbf{R}_h$ and the initial search radius r. We can easily estimate the noise variance and thus ρ can be determined. For $\mathbf{R}_h$, our simulation results demonstrate that we can replace it with an identity matrix with almost no effect on the performance via carrier reordering (see next section). To obtain the initial guess of search radius we can use the strategy described in [17] to determine r that would guarantee a MAP solution with very high probability. More importantly, note that the algorithm itself takes care of the value of r. If it is too small such that the algorithm is not able to backtrack, then it doubles the value of r and if it is too large such that the algorithm reaches the last subcarrier too quickly then it reduces r to the most recent value of objective function. With this self-healing mechanism any choice of r would guarantee the MAP solution.

4 Approximate Blind ML algorithm

As mentioned earlier, the complexity of RLS recursions depends heavily on computation of matrix $\mathbf{P}_i$. We show how we can completely avoid computing $\mathbf{P}_i$ and hence completely discard (23) from RLS recursions.

4.1 Avoiding $\mathbf{P}_i$

We shall assume that $\mathbf{P}_1 = \mathbf{I}$ and that $\mathbf{a}_i$ are orthogonal for $i = 0, 1, 2, \cdots, N-1$, i.e., $\mathbf{a}_i^H \mathbf{a}_j = 0$ for $i \neq j$ [1]. To proceed further, we merge (22) and (23) to get:

$$\mathbf{P}_i = \mathbf{P}_{i-1} - \rho \mathbf{P}_{i-1} \hat{\mathbf{X}}_a^H(i) \boldsymbol{\Gamma}_i^H \hat{\mathbf{X}}_a(i) \mathbf{P}_{i-1} \tag{24}$$

Using our assumptions, we can also show that:

$$\hat{\mathbf{X}}_a(i)\hat{\mathbf{X}}_a^H(j) = \begin{cases} 0 & \text{if } i \neq j \\ L\left(\|\hat{\mathbf{X}}_1(0)\|^2 + \|\hat{\mathbf{X}}_2(0)\|^2\right)\mathbf{I}_2 & \text{if } i = j \end{cases} \tag{25}$$

As proved in [17] for SISO case, it can be easily shown by induction that $\mathbf{P}_i\hat{\mathbf{X}}_a^H(i+1) = \hat{\mathbf{X}}_a^H(i+1)$, $\mathbf{P}_i\hat{\mathbf{X}}_a^H(i+2) = \hat{\mathbf{X}}_a^H(i+2)$ and $\mathbf{P}_{i+1}\hat{\mathbf{X}}_a^H(i+2) = \hat{\mathbf{X}}_a^H(i+2)$. These equations suggest that if successive regressors are orthogonal we can simply replace $\mathbf{P}_i$ with an identity matrix and simply discard equation (23). The new RLS recursions for approximate blind algorithm are:

$$M_{\hat{\mathcal{X}}_{(i)}} = M_{\hat{\mathcal{X}}_{(i-1)}} + \mathbf{e}_i^H \boldsymbol{\Gamma}_i \mathbf{e}_i \tag{26}$$

[1] For things to work a more weaker condition involving only three vectors is enough i.e. $\mathbf{a}_i$, $\mathbf{a}_{i+1}$ and $\mathbf{a}_{i+2}$ are orthogonal.

$$\hat{\mathbf{h}}_i = \hat{\mathbf{h}}_{i-1} + \mathbf{G}_i \mathbf{e}_i \tag{27}$$

where,

$$\mathbf{e}_i = \boldsymbol{\mathcal{Y}}(i) - \sqrt{\rho}\hat{\mathbf{X}}_a(i)\hat{\mathbf{h}}_{i-1} \tag{28}$$

$$\boldsymbol{\Gamma}_i = \frac{1}{1 + \rho L \left(\|\hat{\boldsymbol{\mathcal{X}}}_1(i)\|^2 + \|\hat{\boldsymbol{\mathcal{X}}}_2(i)\|^2 \right)} \mathbf{I}_2 \tag{29}$$

$$\mathbf{G}_i = \sqrt{\rho}\hat{\mathbf{X}}_a(i)^H \boldsymbol{\Gamma}_i \tag{30}$$

We can see that no matrix inversion or computation of $\mathbf{P}_i$ is required any more and the modified algorithm effectively runs at LMS complexity.

4.2 Carrier reordering

Approximate blind algorithm is based on assumption that $\mathbf{P}_1 = \mathbf{I}$ and $\mathbf{a}_i$ are orthogonal which allows us to use (25). It turns out that $\mathbf{a}_i$ are columns of the partial DFT matrix $\mathbf{A}_i$, hence they are not orthogonal. Thus successive regressor matrices would not be orthogonal too. However we can reorder the carriers to make them orthogonal or semi-orthogonal. To explore this, we compute and plot the magnitude of autocorrelation of these partial vectors given by

$$|\mathbf{a}_i^H \mathbf{a}_l| = \begin{cases} L & \text{if } i = l \\ \frac{1}{L}\left|\frac{\sin(\pi(i-1)L/N)}{\sin(\pi(i-1)/N)} \right. & \text{if } i \neq l \end{cases} \tag{31}$$

in Fig. 2 for $N = 16$ and $L = 4$ and where we set $l = 1$. It can be seen that columns $1, 5, 9, 13, \cdots$ are orthogonal to each other and so are the columns $2, 6, 10, 14, \cdots$. Thus if we visit the sub-carriers in order $1, 5, 9, 13, 2, 6, 10, 14, \cdots, 4, 8, 12, 16$ we find that consecutive vectors will be orthogonal or approximately orthogonal. In general, it is found that with $\triangle = N/L$, the vectors $\mathbf{a}_i, \mathbf{a}_{i+\triangle}, \mathbf{a}_{i+2\triangle}, \forall i$ are approximately orthogonal. Thus by simple reordering the carriers we can achieve orthogonality among different sub-carriers and thus use that fact to reduce the complexity of our algorithm as done in previous section. This is allowed in practice because complete OFDM symbol is available to us and we can visit data sub-carriers in any order as we wish.

5 Complexity reduction using reliable carriers

Despite the carrier reordering approach, it has been observed that complexity of algorithm becomes very large in multiple antenna systems as compared to single antenna systems especially at lower SNR. The major source of complexity is attributed to backtracking of proposed algorithm. This issue is rigorously analyzed in [17] where it was shown that probability of backtracking is almost zero at higher SNR, however, no counter measures were proposed to deal with it in the low SNR case. Specifically, the previous approach of reducing the complexity has the following drawbacks:

1 The proposed solution is still very complex as it does not take into account the issue of backtracking which is a major source of complexity. It can be considered to have low complexity only in the high SNR regime, where we get rid of backtracking.

2 The proposed solution does not work in low SNR regime and becomes infeasible for multiple antenna systems. This is due to fact that the search space at each node grows as $|\Omega|^{N_t}$ as compared to $|\Omega|$ in SISO system, where $|\Omega|$ is the alphabet size and N_t is number of transmit antennas. Thus the complexity of the proposed algorithm due to backtracking ultimately dominates the complexity induced by computing the matrix $\mathbf{P}_i$ and becomes the real bottleneck.

3 The proposed solution does not make use of the fact that pilots are usually present in real systems to aid in channel estimation and that the channel is usually slowly varying.

We can make use of third point to our advantage. Specifically the presence of some pilots and slow variation in the channel allows us to get a tentative estimate of the data. If we are able to arrange the data according to its reliability, starting with the most reliable first, then there is a less chance that we need to backtrack. Since earlier data is reliable, there is no need to backtrack for this part. The later data might not be reliable but by the time we start processing this data, the algorithm has already converged. Thus the blind algorithm can be turned into a semi-blind algorithm to track channel variations along with the data detection. The key feature of semi-blind algorithm is that it requires a short training sequence of L symbols only at the start of transmission to get tentative estimate of the data and its reliability and no further pilots or channel statistics are required to be known.

5.1 Measuring reliability

For measuring the reliability of data carriers, we borrow the idea presented in [18] by the author of current paper, where it was used in the context of non-linear distortion mitigation in OFDM. To minimize backtracking, the algorithm must devise a procedure to identify the reliable sub-carriers from the tentative estimates of channel and the data. With receiver having an estimate of channel, the decoding process can be accomplished by rewriting (10) into form as shown below:

$$\acute{\boldsymbol{\mathcal{Y}}} = \sqrt{\rho}\mathbf{H}_a\boldsymbol{\mathcal{X}} + \boldsymbol{\mathcal{N}} \tag{32}$$

where, $\acute{\boldsymbol{\mathcal{Y}}} = [\boldsymbol{\mathcal{Y}}^{(k)}\boldsymbol{\mathcal{Y}}^{*(k+1)}]^T$ and $\mathbf{H}_a$ is an *Alamouti-like* matrix defined as:

$$\mathbf{H}_a \triangleq \begin{bmatrix} \mathbf{\Lambda}_1 & \mathbf{\Lambda}_2 \\ \mathbf{\Lambda}_2^* & -\mathbf{\Lambda}_1^* \end{bmatrix}$$

By left multiplying both sides of (32) with $\sqrt{\rho}\mathbf{H}_a^{-1}$, and re-arranging the terms we get:

$$\hat{\boldsymbol{\mathcal{X}}} = \boldsymbol{\mathcal{X}} + \mathbf{D} \tag{33}$$

where the difference vector; $\mathbf{D} \triangleq \sqrt{\rho}\mathbf{H}_a^{-1}\boldsymbol{\mathcal{N}}$. The imperfect knowledge of the channel results in an estimation error $\Delta\mathbf{H}_a$ and consequently the vector $\mathbf{D}$ represents the distortion due to channel estimation error and the effect of additive noise.

To assess reliability, consider a data carrier $\hat{\boldsymbol{\mathcal{X}}}(k)$ (in scalar case) and its nearest constellation point $\langle\hat{\boldsymbol{\mathcal{X}}}(k)\rangle$. Treating channel estimation error as noise, ML based decoding would yield $\boldsymbol{\mathcal{X}}(k)$ by mapping $\hat{\boldsymbol{\mathcal{X}}}(k)$ to the nearest constellation point $\langle\hat{\boldsymbol{\mathcal{X}}}(k)\rangle$. Such a scheme would be very efficient at higher SNR if distortion were only due to AWGN. However, in our case we have an additional perturbation due to channel estimation error that is independent of SNR and therefore we expect that part of data samples would be severely effected by the distortion and fall outside their actual decision regions. Clearly there is a need to assess and identify these unreliable data coefficients for our algorithm to avoid or reduce backtracking.

Authors in [18] have developed a rigorous method for assessing the reliability of estimated data coefficients. Intuitively, for the data carrier $\hat{\boldsymbol{\mathcal{X}}}(k)$, we can measure its reliability based on relative posterior probability that the difference term D equals $\hat{\boldsymbol{\mathcal{X}}}(k) - \langle\hat{\boldsymbol{\mathcal{X}}}(k)\rangle$ to the probability that it equals some other vector $\hat{\boldsymbol{\mathcal{X}}}(k) - \Omega_m | \Omega \neq \langle\hat{\boldsymbol{\mathcal{X}}}(k)\rangle$ i.e.,

$$R(k) = \frac{Pr\Big(D = \boldsymbol{\mathcal{X}}(k) - \langle\hat{\boldsymbol{\mathcal{X}}}(k)\rangle\Big)}{Pr\Big(D = \boldsymbol{\mathcal{X}}(k) - \Omega(k) | \Omega(k) \neq \langle\hat{\boldsymbol{\mathcal{X}}}(k)\rangle\Big)} \tag{34}$$

The exact expression for reliability is the generalization of scalar-wise ratio in (34) to the vector-wise likelihood ratio defined as:

$$\mathbf{R}^{exact} = \frac{f_D\Big(\mathbf{D} = \boldsymbol{\mathcal{X}} - \langle\hat{\boldsymbol{\mathcal{X}}}\rangle\Big)}{\sum_{m=0, \Omega \neq \langle\hat{\boldsymbol{\mathcal{X}}}\rangle}^{M-1} f_D\Big(\mathbf{D} = \boldsymbol{\mathcal{X}} - \Omega\Big)} \tag{35}$$

where $f_D(.)$ is the *pdf* of distortion vector $\mathbf{D}$, which by definition, can be easily seen to be Gaussian circularly symmetric with variance $\sigma_D^2 = \frac{1}{\rho}\left(\mathbf{Ha}\right)^{-1}\left(\mathbf{Ha}^{-1}\right)^H$. The above computation for exact reliability is however inefficient as it would require $O(NM)$ evaluations of $f_D(.)$ which grows with constellation size M. Alternately, the geometric based approximations for assessing reliability as derived in [18] may be employed with marginal loss in the performance. Ultimately, we compute the reliability associated with each data subcarrier which allows us to select the most reliable ones. We shall often use the term reliability measure as the number of the most reliable carriers (in percentage) supplied (after reordering) to our algorithm for initial search of the ML solution.

5.2 Slow fading channel model

The AR(1) model is often used to model the slow rayleigh fading channel with satisfactory accuracy. Thus removing the subscripts the variations in the channel weight vector of each transmit-receive pair can be modelled as [19]:

$$\mathbf{h}(n) = \alpha\mathbf{h}(n-1) + \mathbf{q}(n) \tag{36}$$

where $\alpha = J_0(2\pi f_d T_s)$ and $\mathbf{q}$ is complex normal vector with covariance matrix $(1-\alpha^2)\mathbf{I}$. The product of maximum Doppler frequency f_d and sampling time T_s, referred to as normalized doppler frequency F_D, controls the amount of variations in the channel coefficients.

5.3 The Semi-blind algorithm

Based on above developments we can cast our semi-blind algorithm which involves the following steps:

1 Obtain an initial estimate of channel vector $\mathbf{h}$ from L training/pilot symbols at start of transmission, then repeat the following steps over two consecutive time instants.

2 Predict and decode the carriers $\hat{\boldsymbol{\mathcal{X}}}$ from previous channel estimate $\hat{\mathbf{h}}$ and observation vector $\boldsymbol{\mathcal{Y}}$.

3 Use (35) to compute reliability of carriers and reorder them in decreasing order of their reliability measurements.

4 Run blind-algorithm proposed previously to obtain exact ML estimates of channel and data.

Remarks: The first three steps of the semi-blind algorithm serve as pre-processing steps tailored to minimizing the backtracking of blind algorithm in step 4. To obtain channel estimate from pilots in step 1, one can use RLS algorithm starting from zero initial conditions and $\mathbf{P}_i = \mathbf{I}$. Moreover, the step 1 is computed only once at the start of transmission when pilots are used, thus the RLS recursions would add little to overall computation of algorithm. The prediction step (2) is trivial and would suffer only little distortion as the channel does not change much in slow fading. To initiate the RLS recursions of blind algorithm we initialize the channel vector with its previous estimate and set $\mathbf{P}_i = \mathbf{I}$; thus no channel statistics are required to be known *a priori*. With carriers credibilities at hand, the tree-search mechanism of blind algorithm step (4), can be judiciously modified to nearest neighbour rule to reduce the backtracking at subcarrier levels. Also observe that the carrier reordering does not ensure orthogonality of successive regressors therefore, the low complexity variants of RLS recursions are no more valid.

6 Simulation results

For simulations we first consider OFDM system with $N = 16$ subcarriers and channel length $L = 4$ for each transmit-receive channel and CP length of at least L-1. For blind algorithm, both channels are independent Rayleigh fading, assumed stationary over two consecutive OFDM blocks and each having an exponential power decay profile i.e. $E\left\{|h_i(t)|^2\right\} = e^{-0.2t}$. Information symbols are modulated using BPSK or 4-QAM.

In Fig. 3 we plot the results for $N = 16$, BPSK data symbols using perfectly known channel and our exact blind algorithm, together with low-complexity variants, i.e. blind algorithm with (a)$\mathbf{P}_i = \mathbf{I}$ (b) $\mathbf{P}_i = \mathbf{I}$ with subcarrier reordering. In first case the performance degrades and BER reaches an error floor. However, with subcarrier reordering approach we almost get the same performance as that of exact blind algorithm without requiring the channel statistics. Similar trend is observed in Fig. 4, when 4-QAM signal modulation is considered.

For semi-blind algorithm we considered two different values of normalized doppler frequency; $F_D = f_d T_s = 0.1$ and 0.001, to model relatively fast and slow fading channels respectively. Simulation results for semi-blind algorithm are depicted in figures 5, 6 and 7 for BPSK and 4$-$QAM modulations which show favourable performance of algorithm under different fading conditions. The results for SISO-OFDM system are also given in figures 8, 9, and 10 for comparison with previous work on SISO systems. The results demonstrate good performance under different fading conditions.

To assess the computational complexity of proposed algorithm, we compare average run-time of algorithm with various reliability measures in Fig. 11. It is clearly observed that proposed reliability scheme offers significantly lower complexity at lower SNR values. At higher SNR values the run time is constant for all, confirming the fact that there is almost no backtracking. In Fig. 12 and Fig. 13 we plot BER and average computation time for various degrees of reliability. The performance for various degrees of reliability measures is almost identical however as evident from Fig. 13 we are able to get significant reduction in complexity. We see that using reliability greater than 70% does not help much in reducing the complexity because the probability of later data being reliable would be very low and would result in more backtracking. From Fig. 13 we conclude that the reliability of around

50-60 percent is enough for a good performance, although more importantly, the algorithm doesn't disfavour the usage of more reliable carriers.

Fig. 14 compares the average run-time for different modulation schemes such as BPSK, 4-QAM and 16-QAM. These result clearly indicate the computational advantage of proposed reliability-based method.

7 Conclusion

In this paper we presented a blind ML algorithm for joint channel estimation and data detection in OFDM wireless systems using STBC coding. Simulation results show favourable performance of algorithm. As evident from simulations, our low complexity blind algorithm performs equally well as exact blind algorithm. Moreover, the new algorithm doesn't need any prior information about channel statistics as it avoids calculating matrix $\mathbf{P}_i$ with subcarrier reordering. Another major source of complexity in blind algorithm is the issue of backtracking which was not dealt with in previous studies at low SNR regime. We proposed a semi-blind algorithm which minimizes the probability of backtracking by supplying the blind algorithm with reordered sub-carriers based on their reliability computations using a sophisticated reliability criterion. By minimizing the backtracking, significant improvement is achieved in terms of complexity without compromising the performance. The proposed algorithm requires short training sequence and assumes channel statistics to be unknown. Simulation results for semi-blind algorithm show good performance over channels with different fading characteristics.

Competing interests

The authors declare that they have no competing interests.

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Additional Files

Additional file 1 — Reference PDF

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The 'TEX' file for figures of manuscript.

Additional file 3 — Figures PDF

The 'PDF' file containing all figures of manuscript.

Additional file 4 — biblio blindML

Contains the bibliography for manuscript (uploading this file as a dependent file was leading to errors by the upload system).

Figures

Figure 1 Alamouti coded OFDM system

Figure 2 Autocorrelation as a function of i for N=16 and L=4

Figure 3 BER Vs SNR for Alamouti-coded BPSK OFDM over Rayleigh fading channel with N=16 and L=4

Figure 4 BER Vs SNR for Alamouti-coded 4-QAM OFDM over Rayleigh fading channel with N=16 and L=4

Figure 5 BER Vs SNR for MISO-OFDM with BPSK modulation over Rayleigh fading channel with N=16 and L=4

Figure 6 BER Vs SNR for MISO-OFDM with BPSK modulation over Rayleigh fading channel with N=32 and L=4

Figure 7 BER Vs SNR for MISO-OFDM with 4-QAM modulaton over Rayleigh fading channel with N=32 and L=4

Figure 8 BER Vs SNR for SISO-OFDM with BPSK modulation over Rayleigh fading channel with N=64 and L=8

Figure 9 BER Vs SNR for SISO-OFDM with 4-QAM modulation over Rayleigh fading channel with N=64 and L=8

Figure 10 BER Vs SNR for SISO-OFDM with 16-QAM modulation over Rayleigh fading channel with N=64 and L=4

Figure 11 Average Run Time of proposed semi-blind algorithm for BPSK modulation with N=16 and L=4

Figure 12 Performance of proposed algorithm with various degrees of reliability measurements (BPSK modulation with N=16 and L=4)

Figure 13 Avgerage Run Time of proposed algorithm with various degrees of reliability measurements (BPSK modulation with N=16 and L=4)

Figure 14 Average Run Time of proposed semi-blind algorithm for different modulations with N=16 and L=4. Proposed semiblind algorithm without (solid lines) and with reliable carriers (dashed lines)

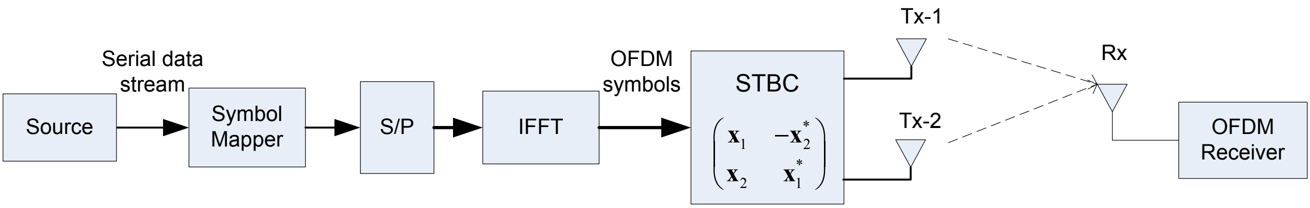
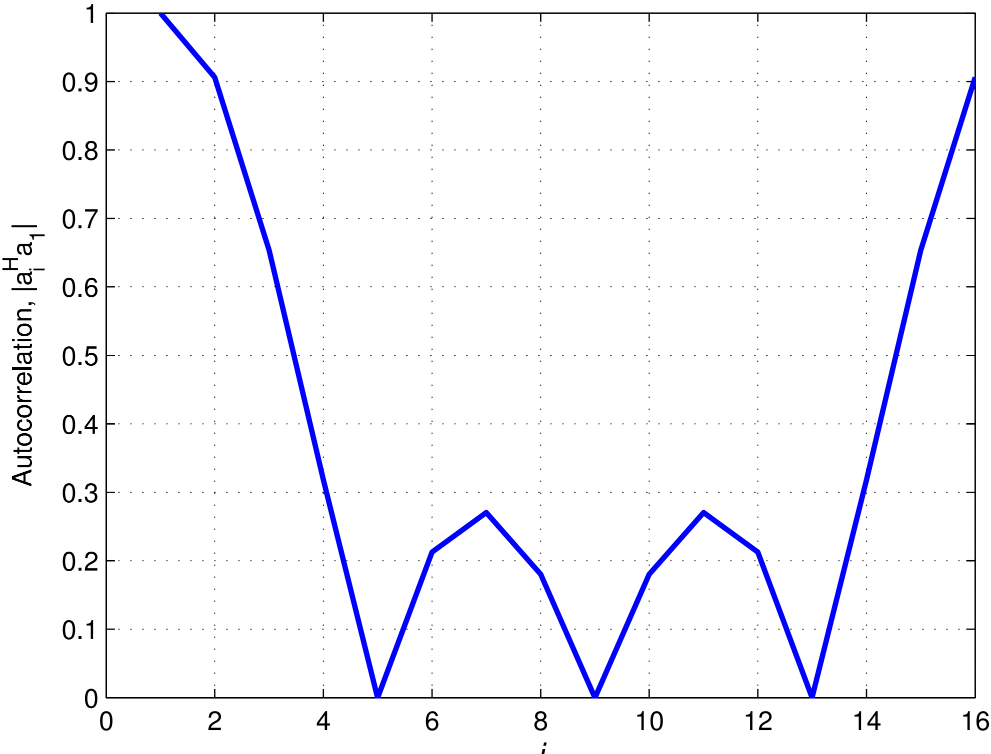
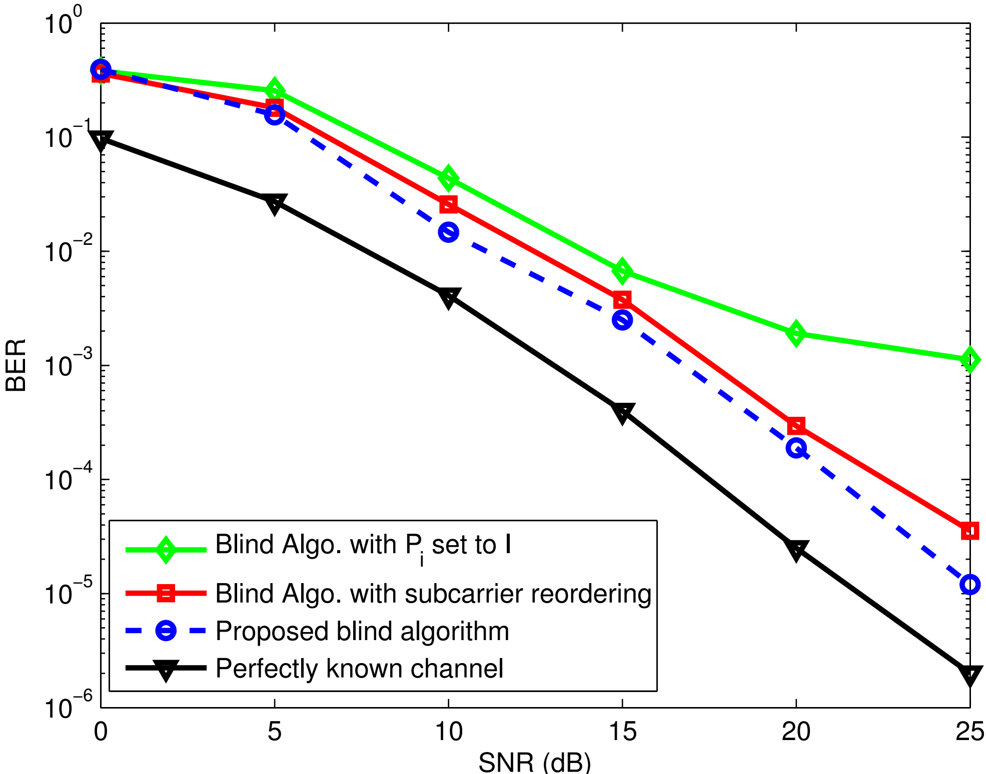

Serial data stream
Source
Symbol Mapper
S/P
IFFT
OFDM symbols
STBC
$\begin{pmatrix} \mathbf{x}_1 & -\mathbf{x}_2^* \\ \mathbf{x}_2 & \mathbf{x}_1^* \end{pmatrix}$
Tx-1
Tx-2
Rx
OFDM Receiver

Figure 1



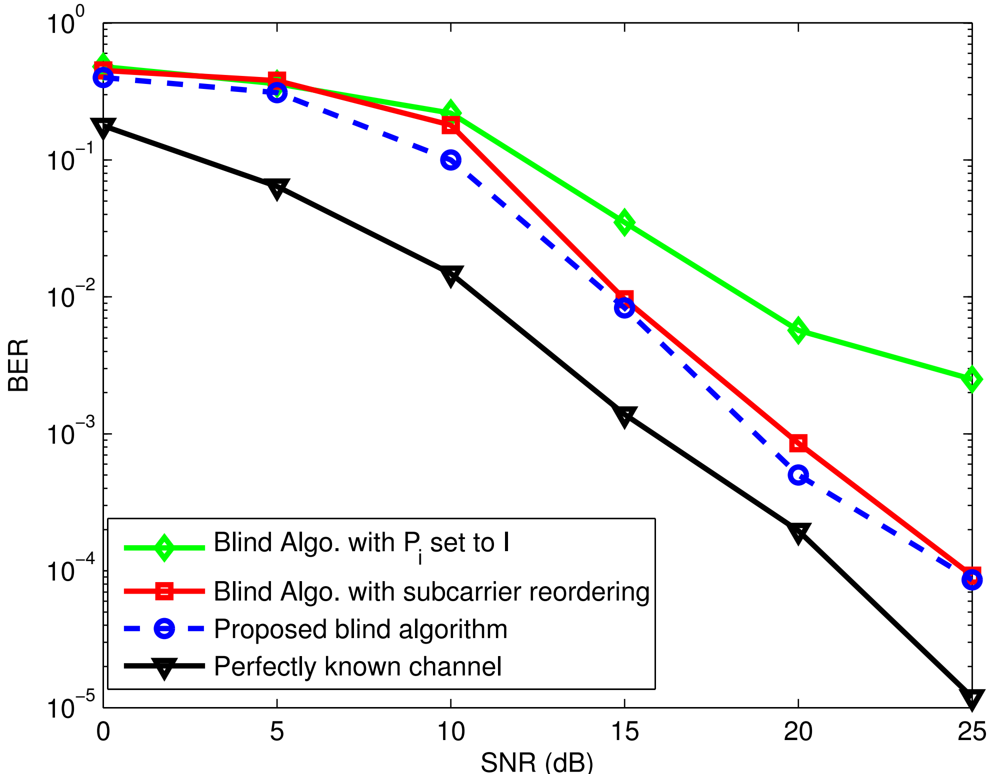
Autocorrelation, $|a_i^H a_1|$
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
2
4
6
8
10
12
14
16
i

Figure 2



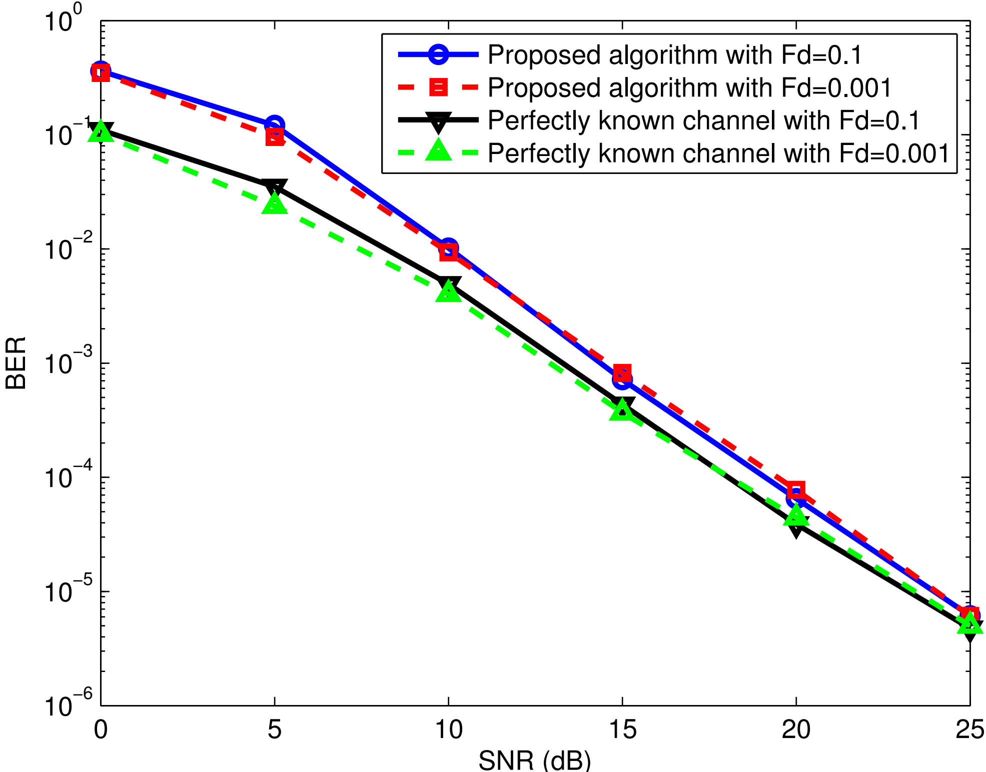
BER
SNR (dB)
Blind Algo. with P_i set to I
Blind Algo. with subcarrier reordering
Proposed blind algorithm
Perfectly known channel

Figure 3



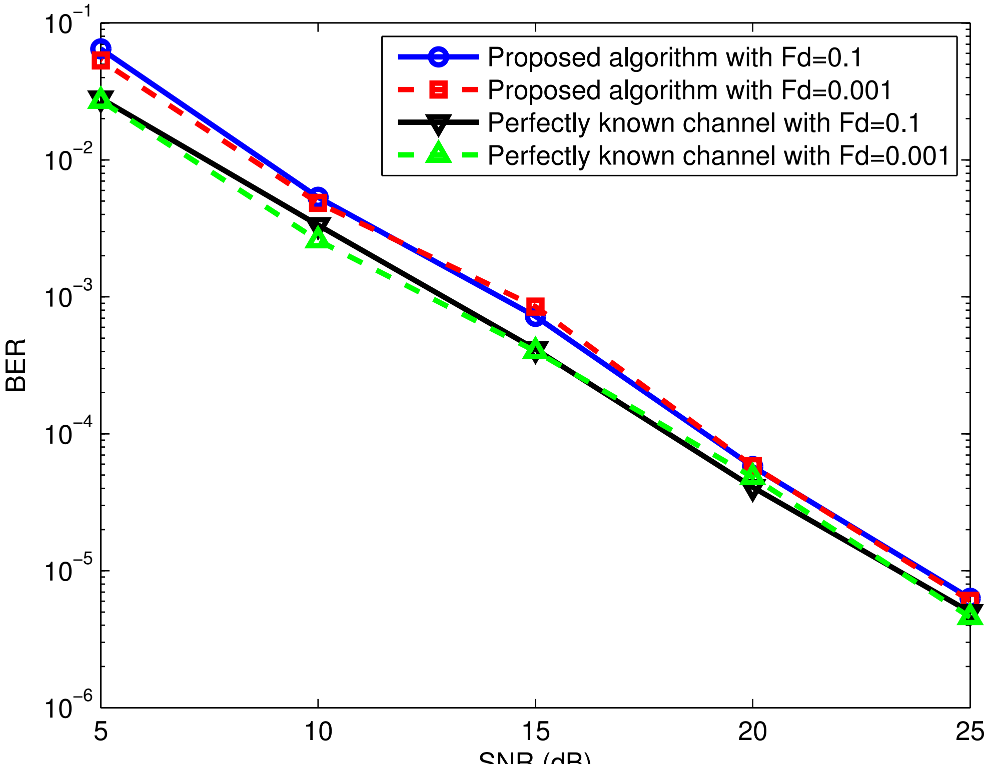
BER
SNR (dB)
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
0
5
10
15
20
25
Blind Algo. with P_i set to I
Blind Algo. with subcarrier reordering
Proposed blind algorithm
Perfectly known channel

Figure 4



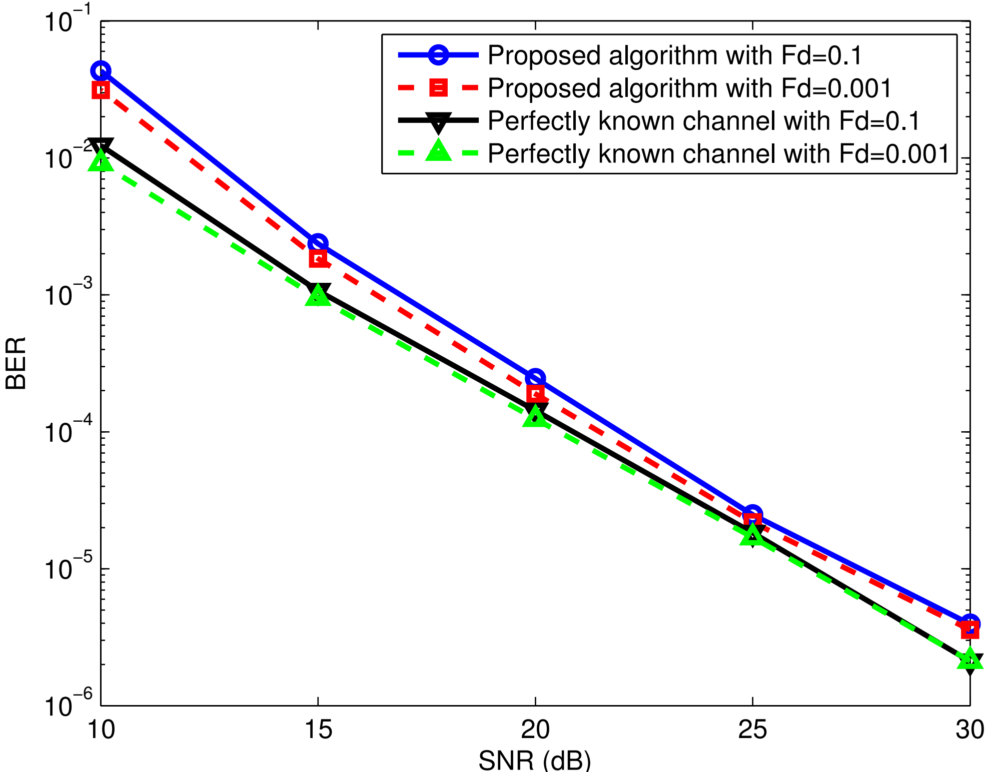
Proposed algorithm with Fd=0.1
Proposed algorithm with Fd=0.001
Perfectly known channel with Fd=0.1
Perfectly known channel with Fd=0.001
BER
SNR (dB)
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
0
5
10
15
20
25

Figure 5



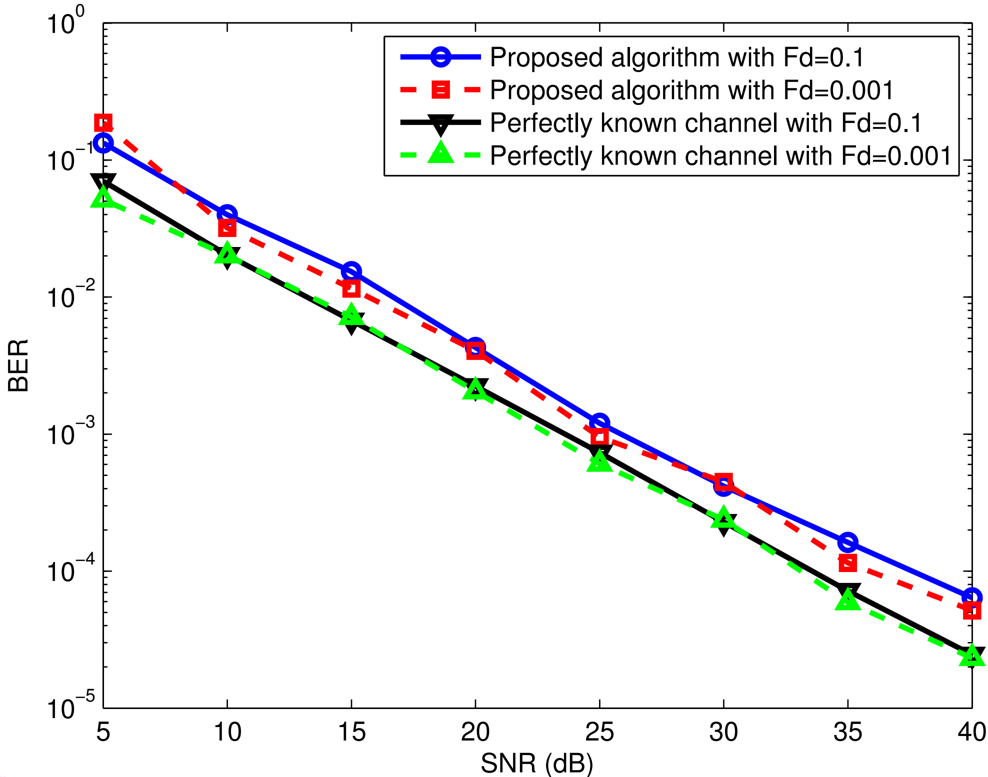
Proposed algorithm with Fd=0.1
Proposed algorithm with Fd=0.001
Perfectly known channel with Fd=0.1
Perfectly known channel with Fd=0.001
BER
SNR (dB)
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
5
10
15
20
25

Figure 6



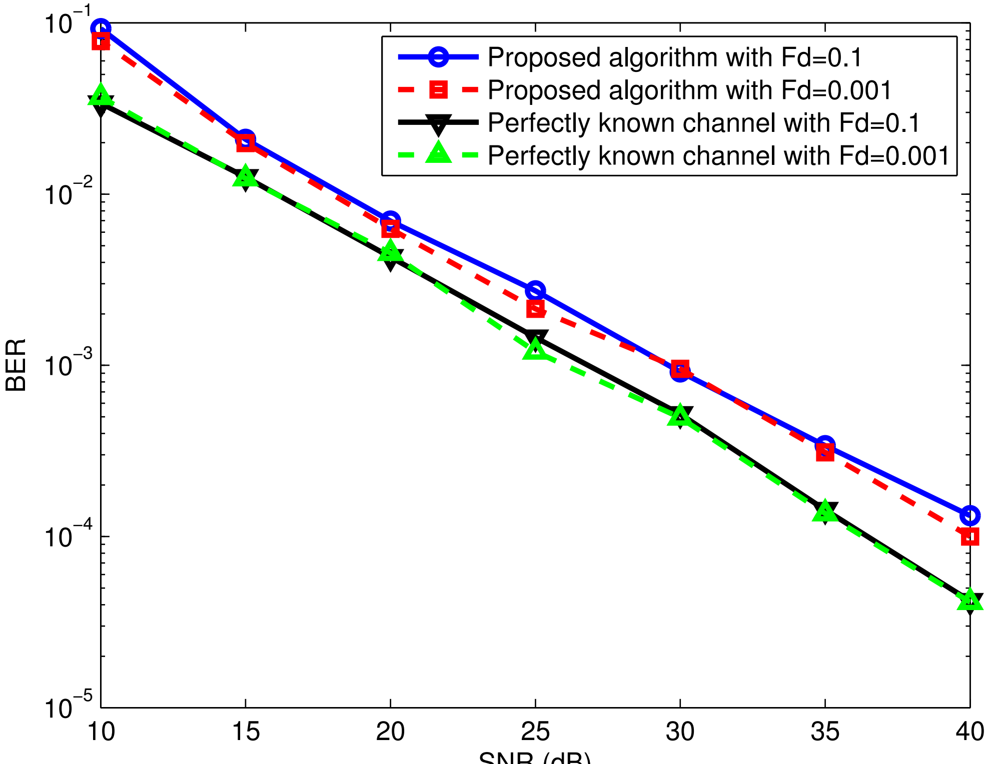
Proposed algorithm with Fd=0.1
Proposed algorithm with Fd=0.001
Perfectly known channel with Fd=0.1
Perfectly known channel with Fd=0.001
BER
SNR (dB)
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10
15
20
25
30

Figure 7



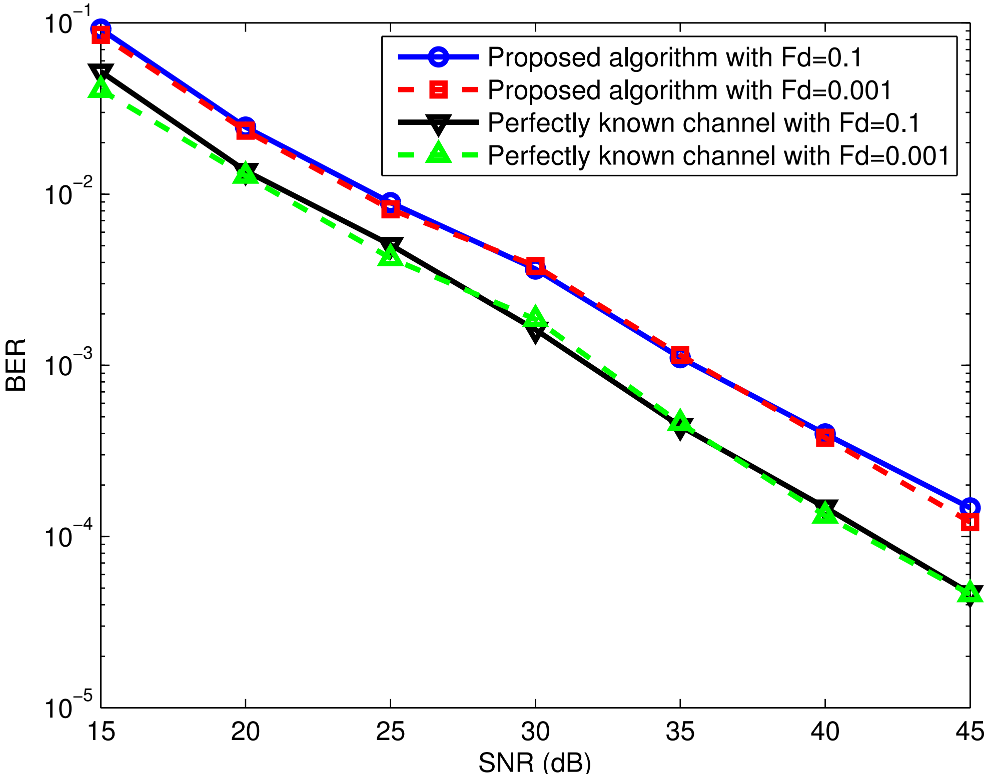
Proposed algorithm with Fd=0.1
Proposed algorithm with Fd=0.001
Perfectly known channel with Fd=0.1
Perfectly known channel with Fd=0.001
BER
SNR (dB)
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
5
10
15
20
25
30
35
40

Figure 8



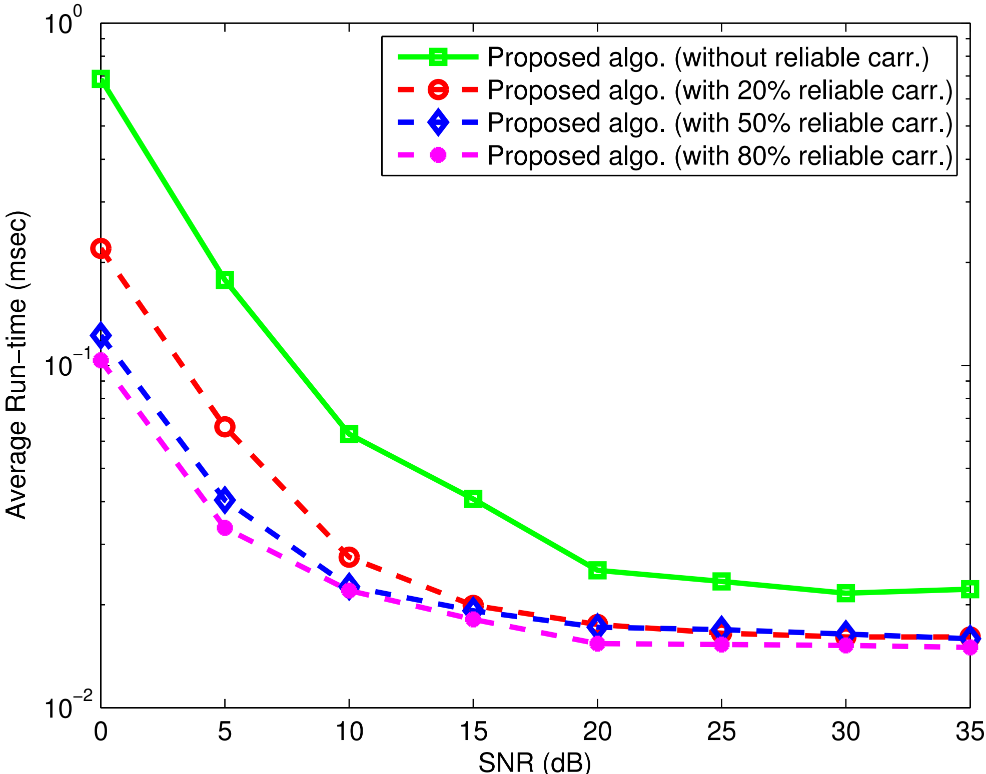
Proposed algorithm with Fd=0.1
Proposed algorithm with Fd=0.001
Perfectly known channel with Fd=0.1
Perfectly known channel with Fd=0.001
BER
SNR (dB)
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10
15
20
25
30
35
40

Figure 9



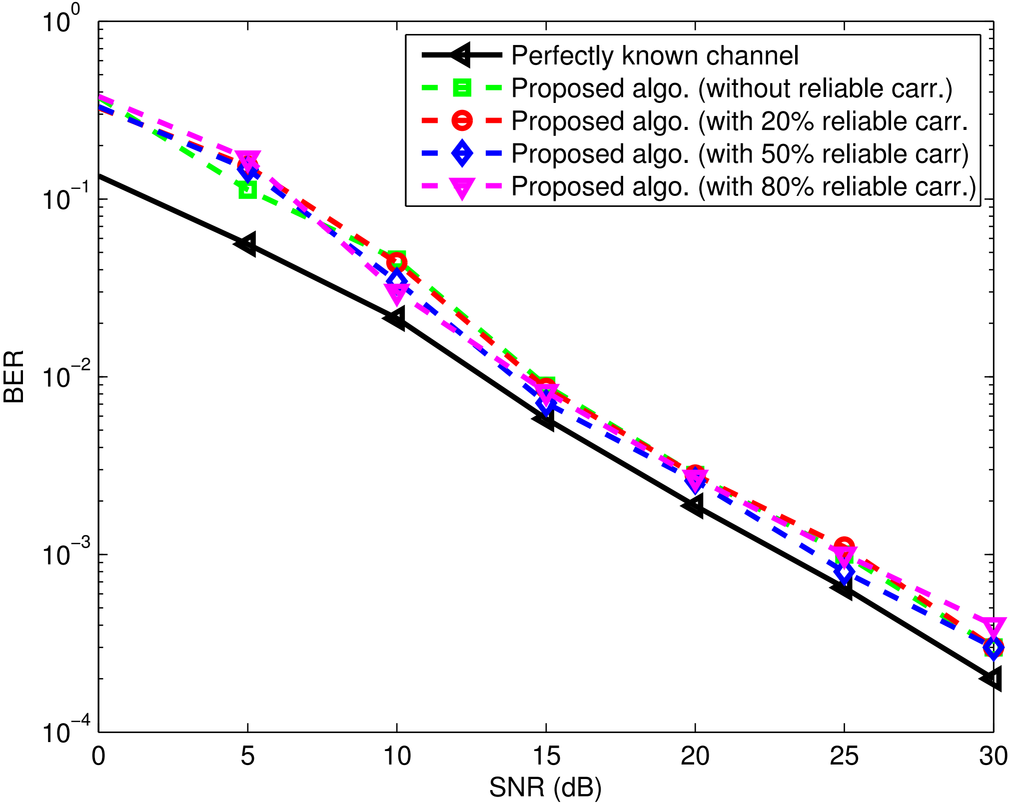
Proposed algorithm with Fd=0.1
Proposed algorithm with Fd=0.001
Perfectly known channel with Fd=0.1
Perfectly known channel with Fd=0.001
BER
SNR (dB)
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-5}
15
20
25
30
35
40
45

Figure 10



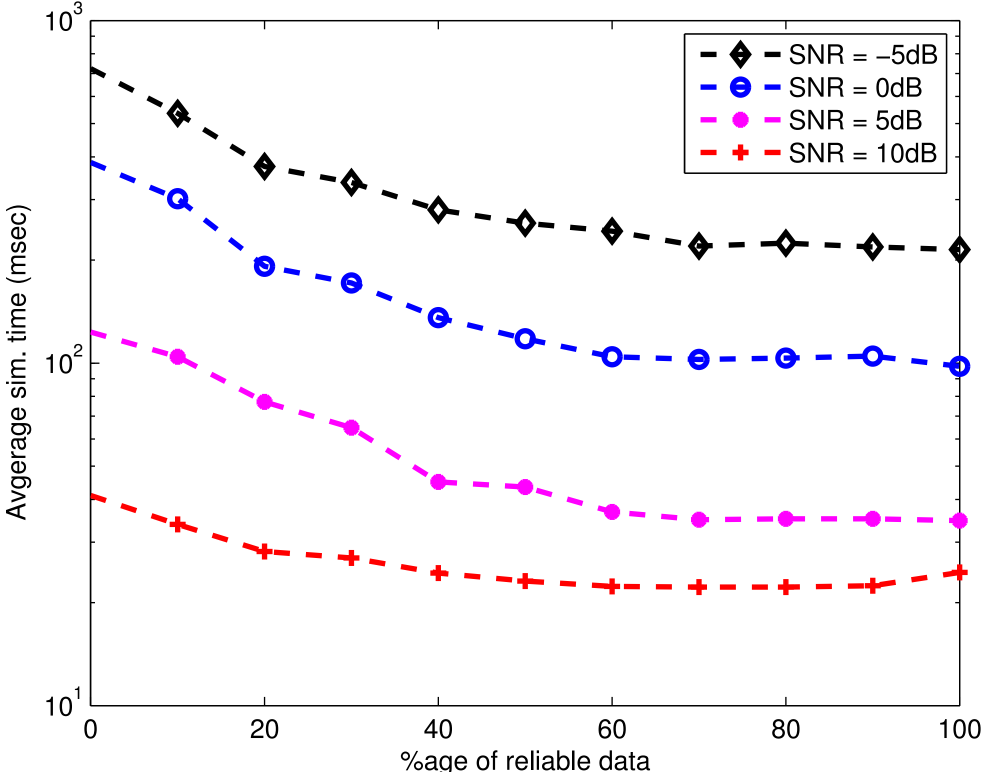
Proposed algo. (without reliable carr.)
Proposed algo. (with 20% reliable carr.)
Proposed algo. (with 50% reliable carr.)
Proposed algo. (with 80% reliable carr.)
Average Run−time (msec)
10^0
10^{-1}
10^{-2}
0
5
10
15
20
25
30
35
SNR (dB)

Figure 11



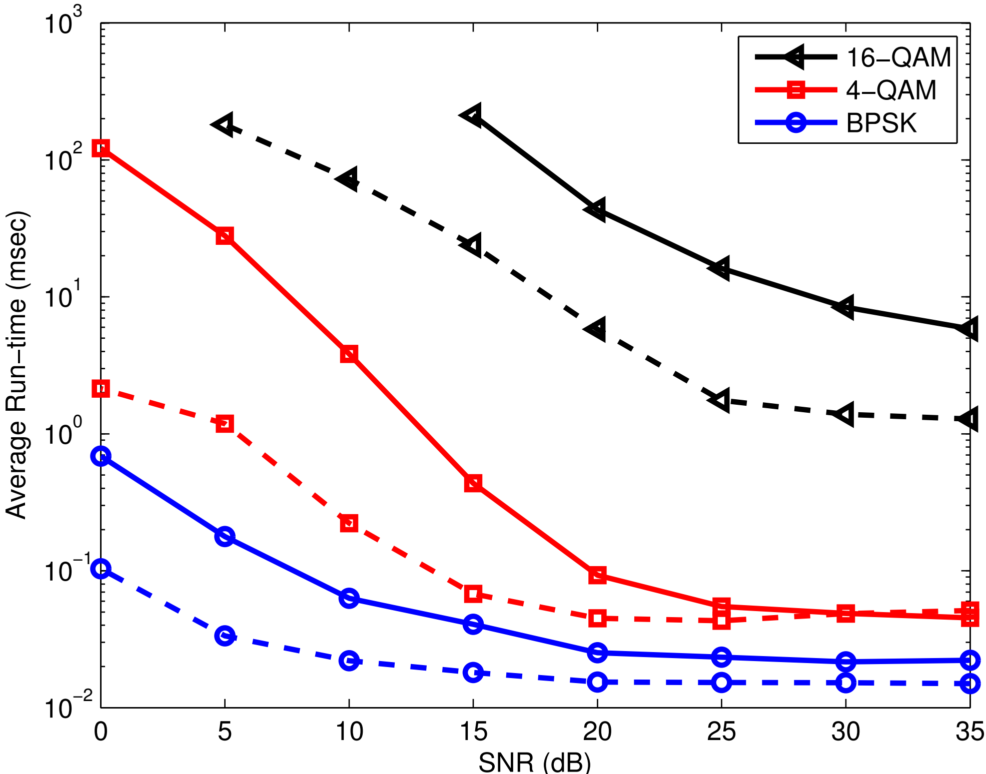
Perfectly known channel
Proposed algo. (without reliable carr.)
Proposed algo. (with 20% reliable carr.
Proposed algo. (with 50% reliable carr)
Proposed algo. (with 80% reliable carr.)
BER
SNR (dB)
10^{0}
10^{-1}
10^{-2}
10^{-3}
10^{-4}
0
5
10
15
20
25
30

Figure 12



SNR = −5dB
SNR = 0dB
SNR = 5dB
SNR = 10dB
Avgerage sim. time (msec)
%age of reliable data
10^3
10^2
10^1
0
20
40
60
80
100

Figure 13



16−QAM
4−QAM
BPSK
Average Run−time (msec)
10^{3}
10^{2}
10^{1}
10^{0}
10^{-1}
10^{-2}
0
5
10
15
20
25
30
35
SNR (dB)

Figure 14

Additional files provided with this submission:

Additional file 1: Reference PDF.pdf, 184K
http://asp.eurasipjournals.com/imedia/1008498146113315/supp1.pdf
Additional file 2: Figures.tex, 3K
http://asp.eurasipjournals.com/imedia/1683209204113316/supp2.tex
Additional file 3: Figures.pdf, 113K
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